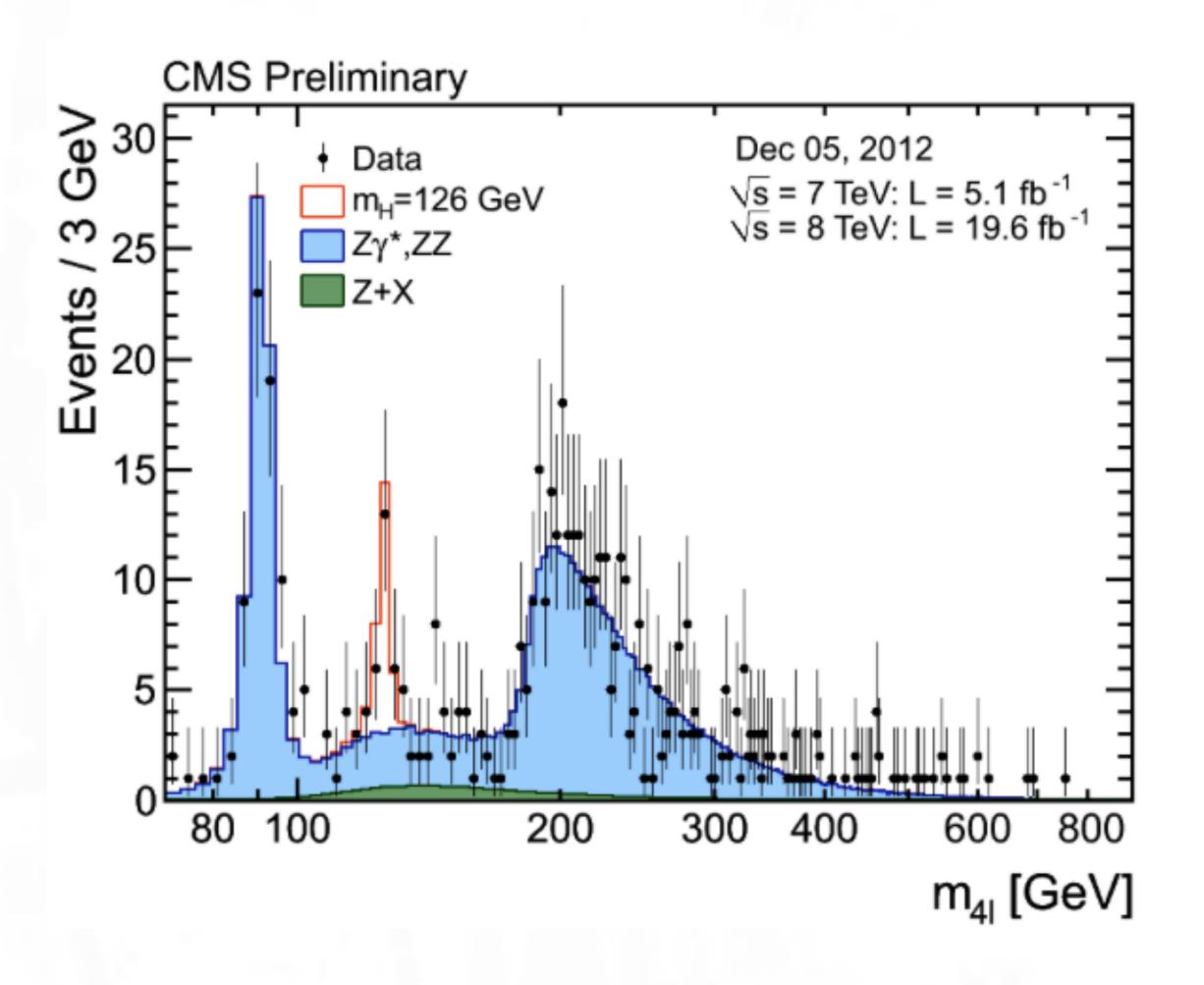


Infrastructure for Large Scale HEP data analysis

Matteo Cremonesi **FNAL**

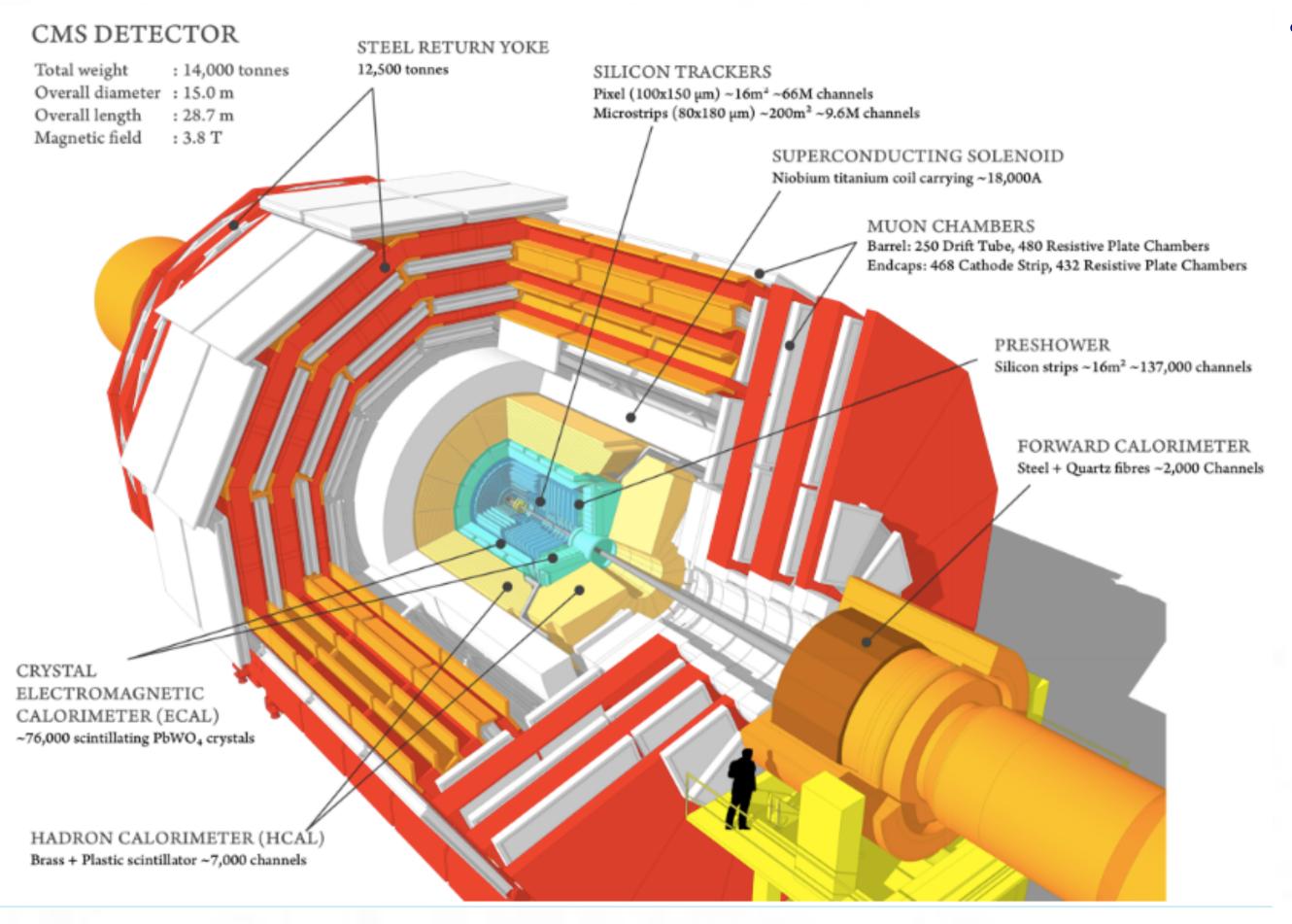
DS@HEP - May 11, 2017

Experimental Particle Physics

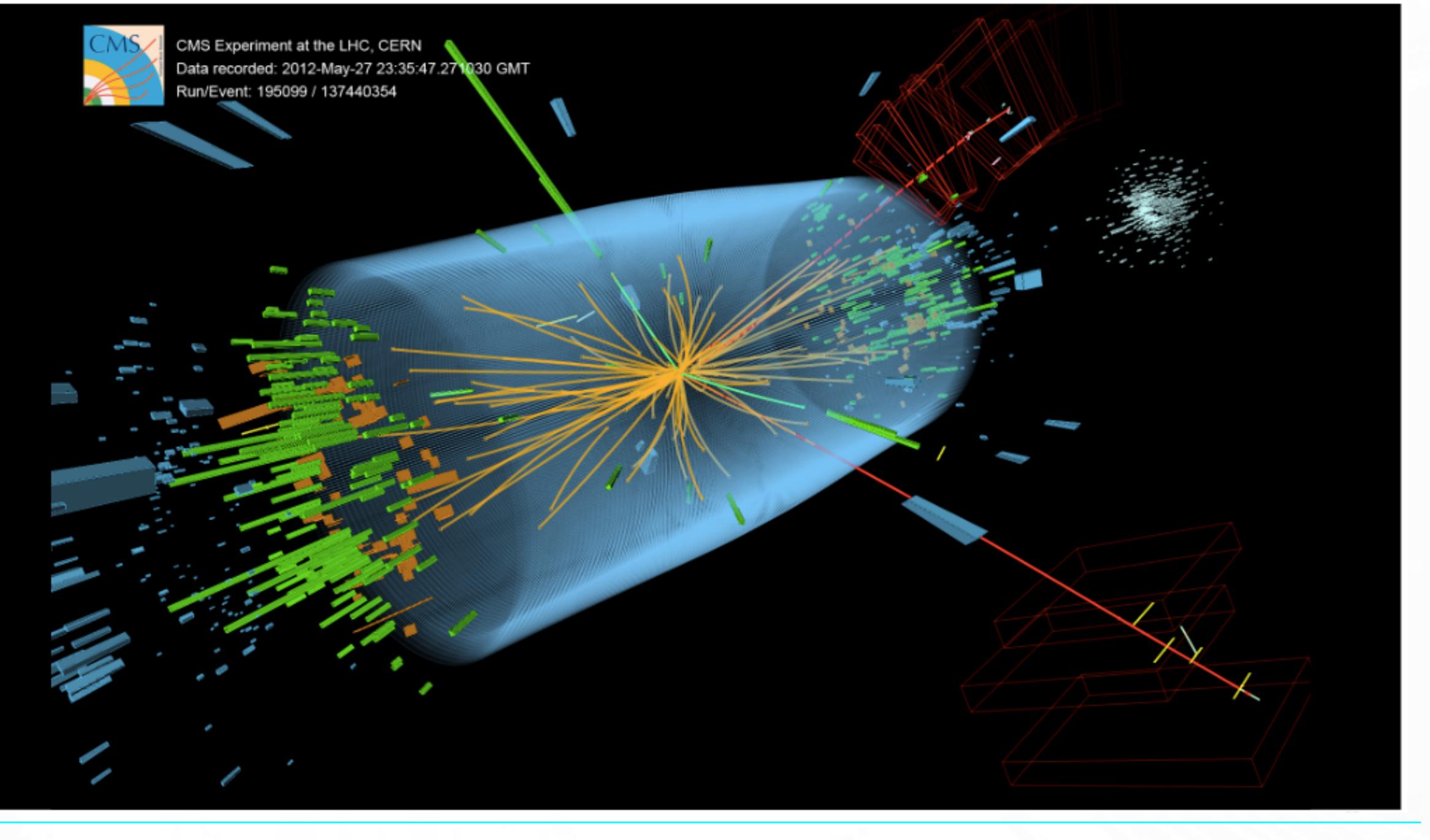


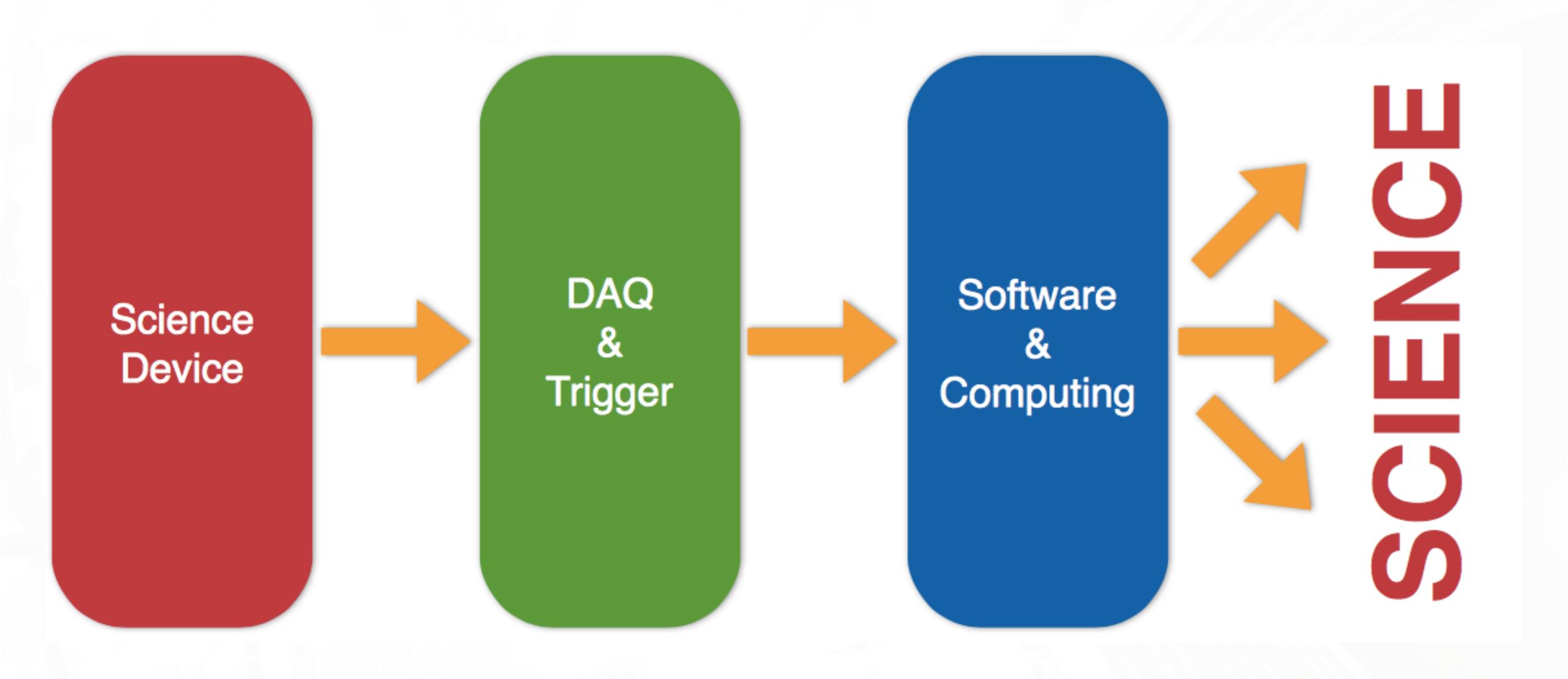
- Detect particle interactions (data), compare with theory predictions (simulation)
 - Black dots: recorded data
 - Blue shape: simulation
 - Red shape: simulation of new theory (in this case the Higgs)

Data Events

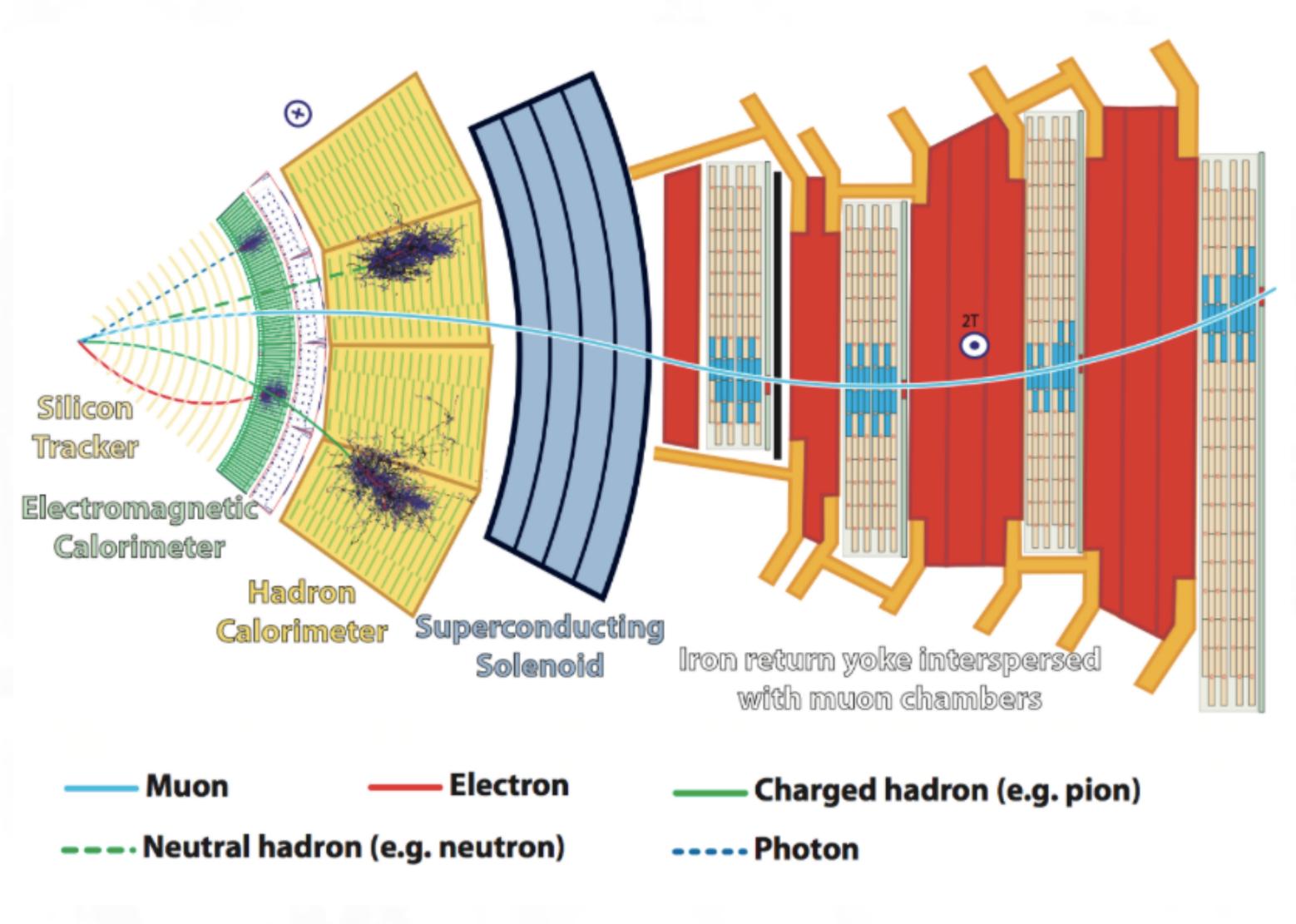


- Particle detection = record physics quantities (energy, flight path) of particles produced in a collision
 - Quantities measured from the interaction of particles and the different detector components
 - 100 Million individual measurements
 - All measurements of a collision together are called event

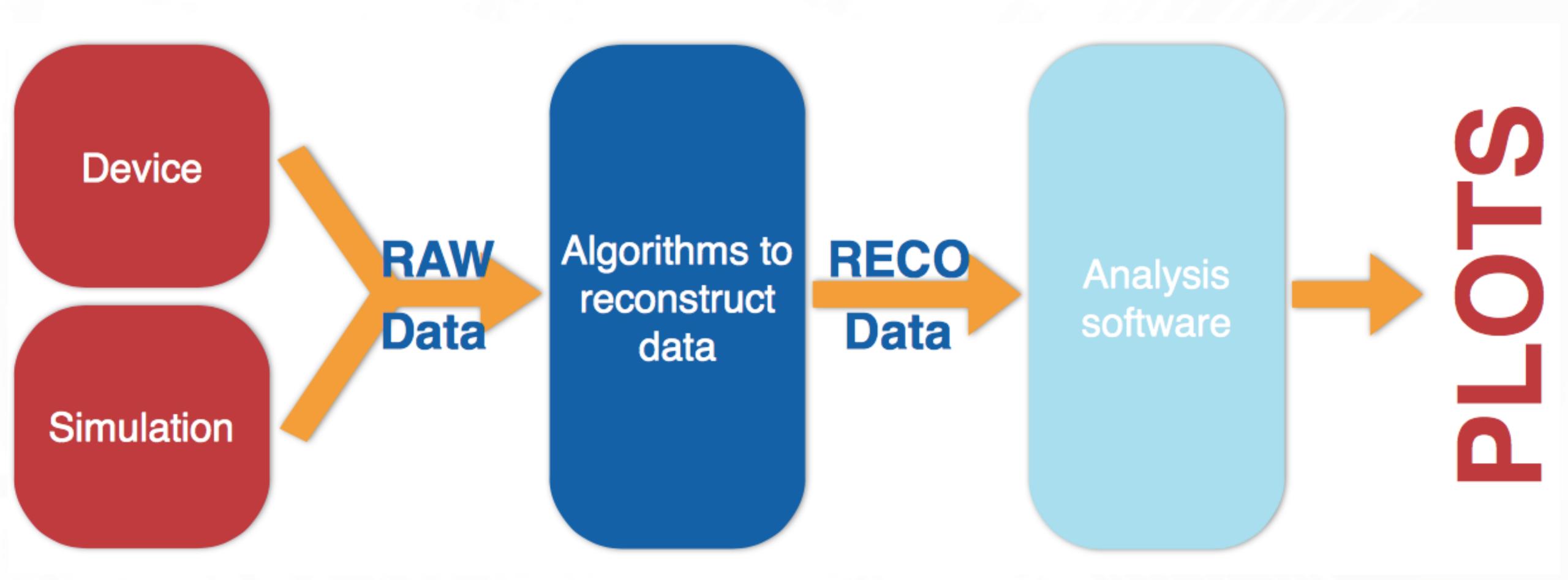


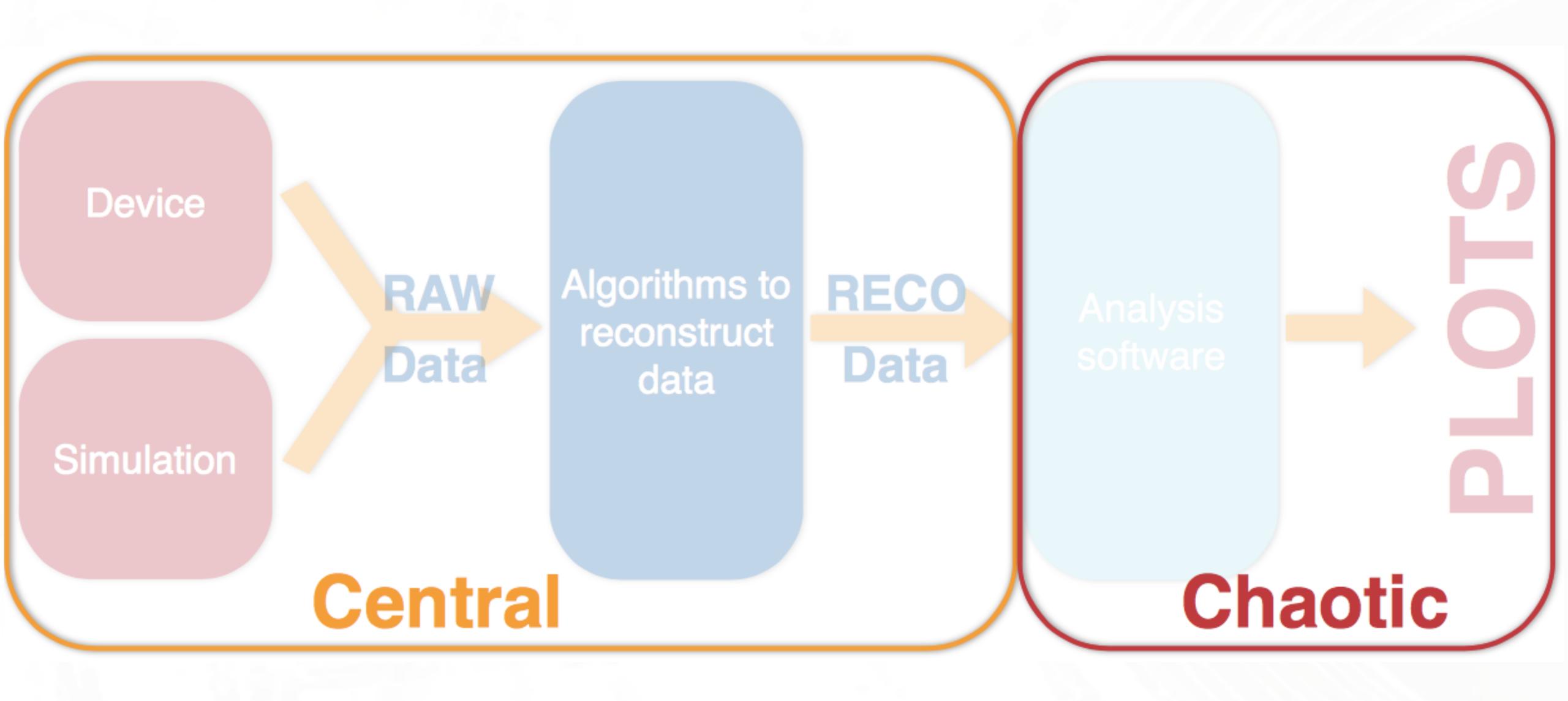


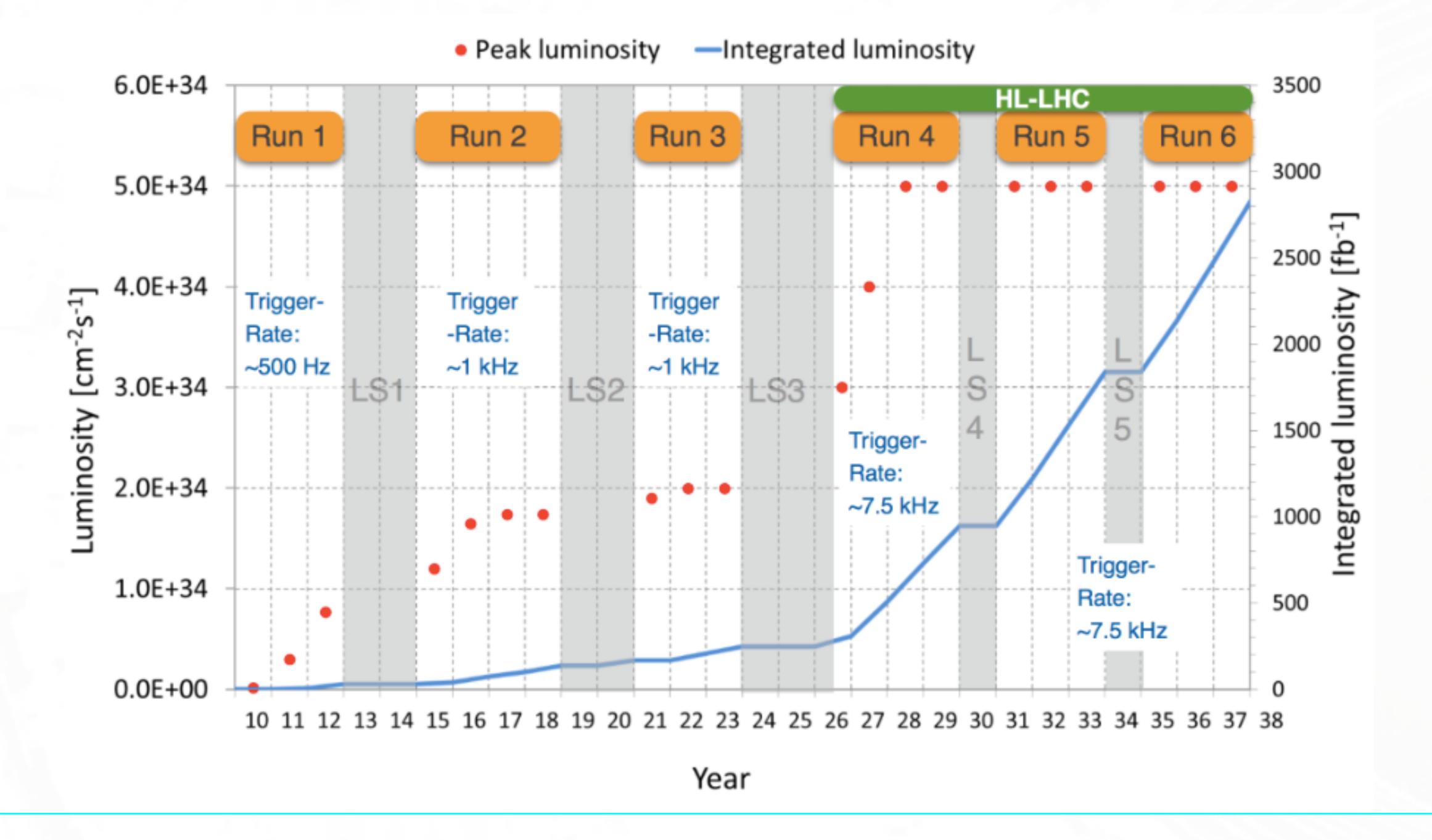
Event Reconstruction



- Detector signals (and equivalent simulated signals) need to be reconstructed to learn about the particles that produced them
- The reconstructed events are then used for analysis

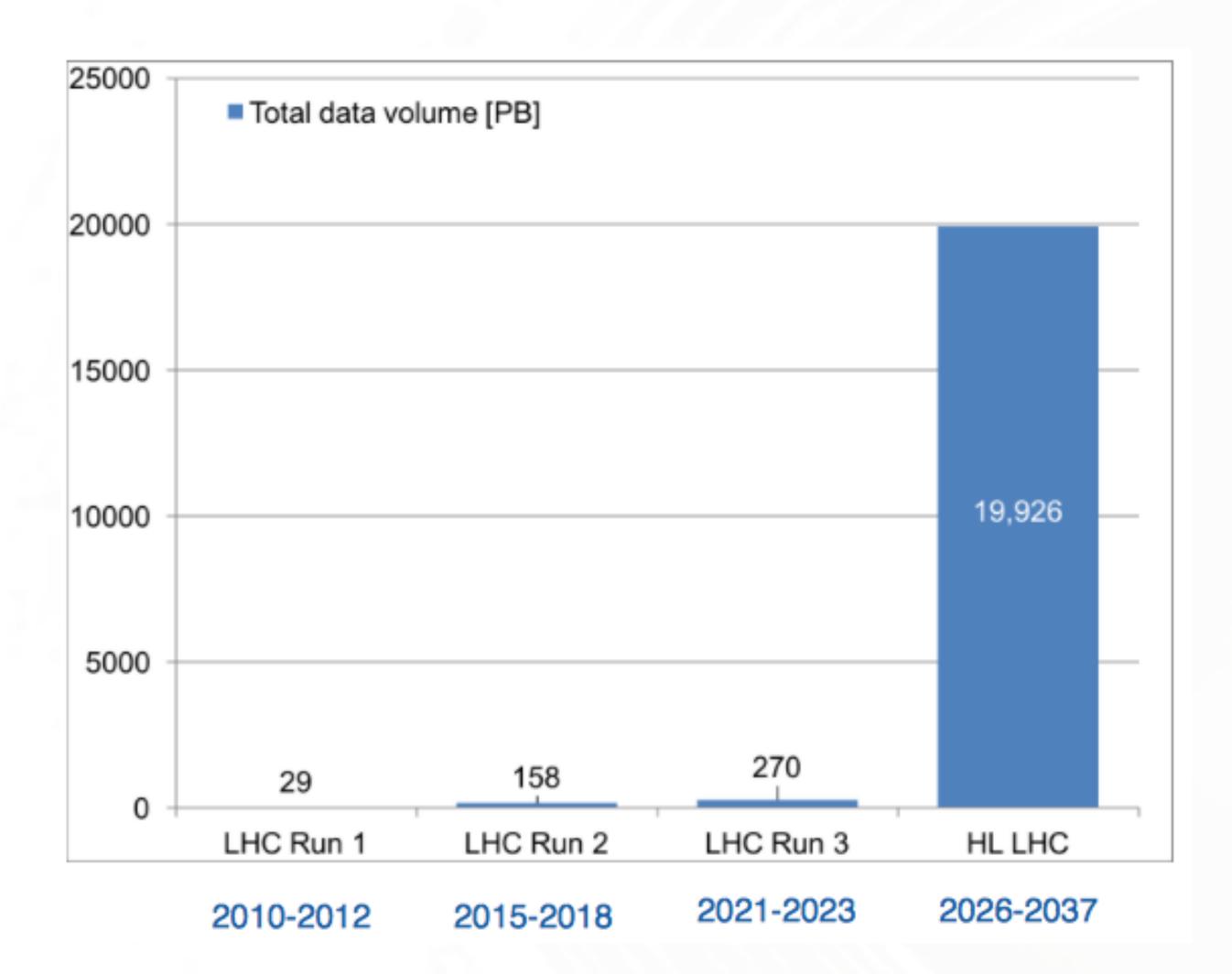






Data Volume @ HL-LHC

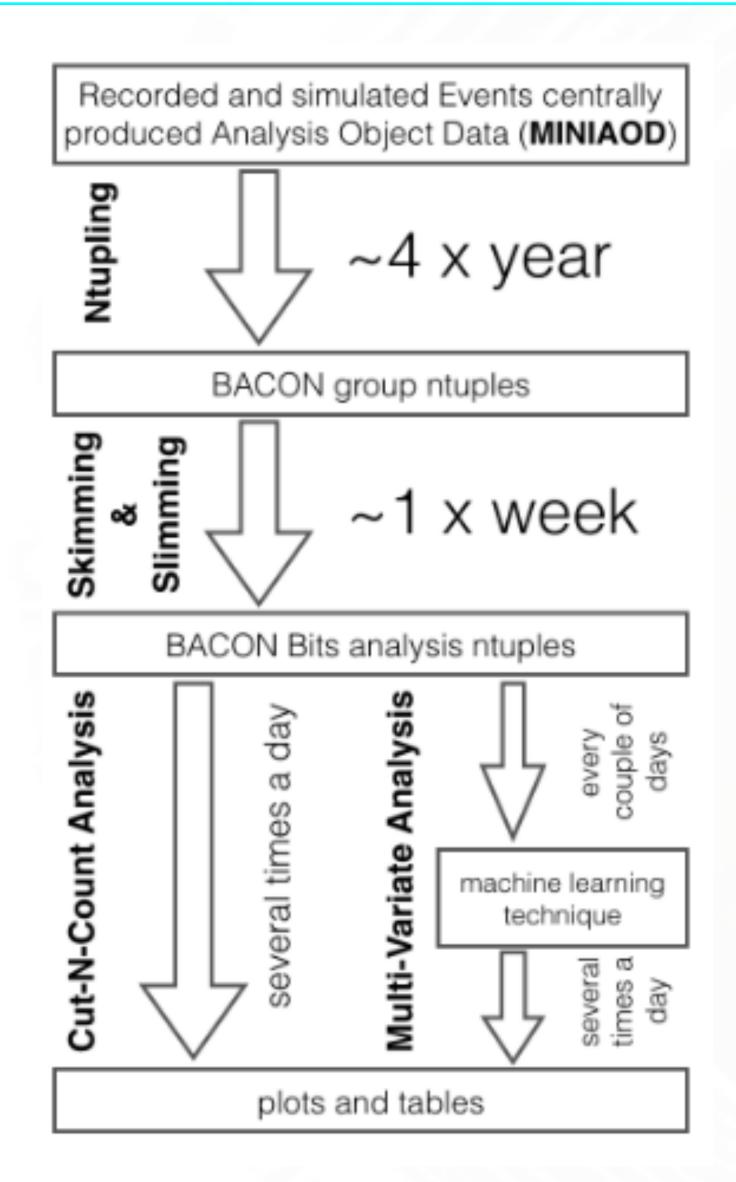
- Extract physics results will require to handle/analyze a lot more data
 - you cannot afford chaos anymore
- Explore industry technologies as suitable candidates for user analysis



Current Analysis Workflow

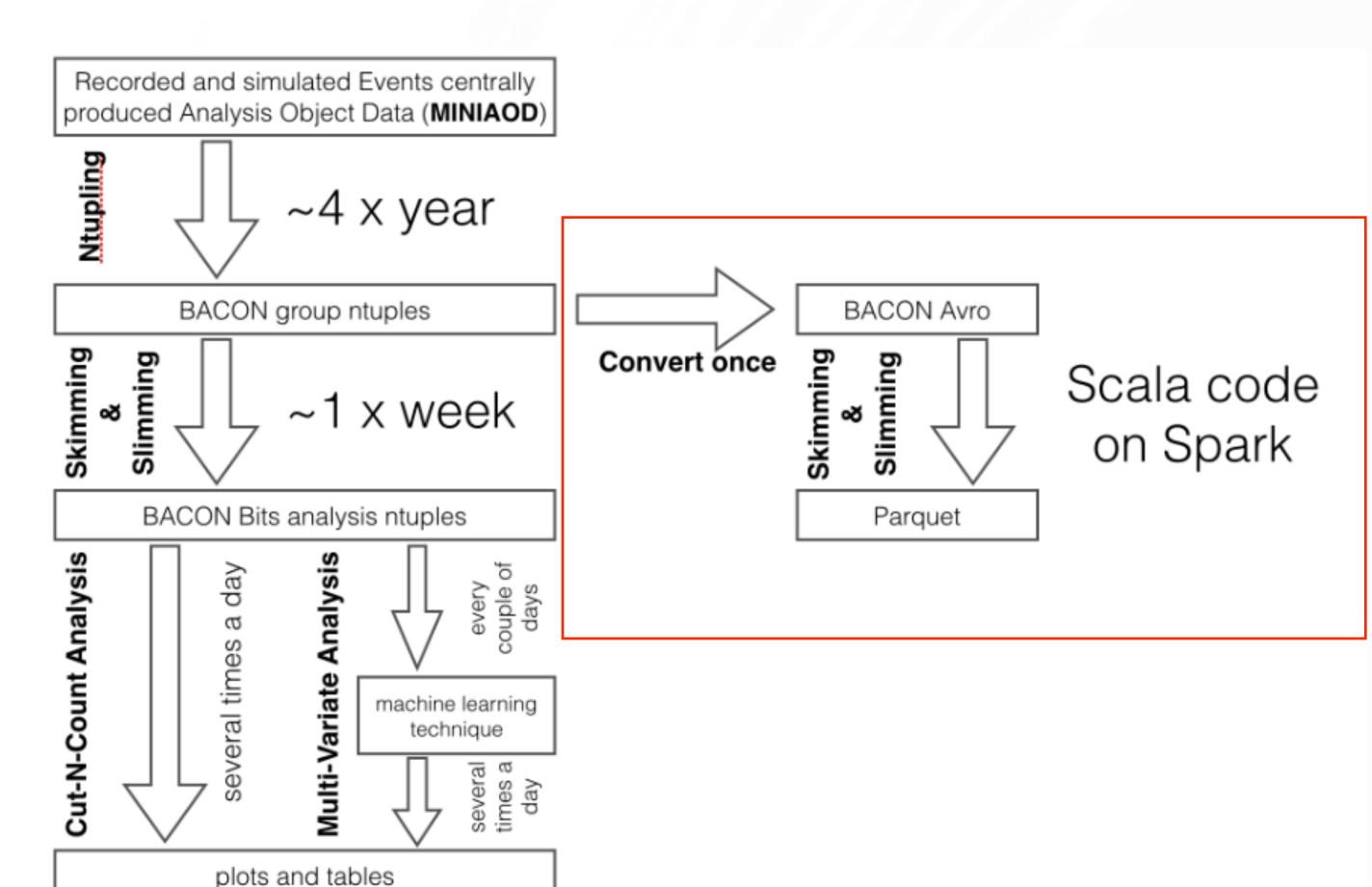
Input:

- Centrally produced output of reconstruction software, reduced content optimized for analysis
- Apply updated CMS reconstruction recipes
- Too big for interactive analysis
- Ntupling:
 - Convert into format suited for interactive analysis
 - Still too big for interactive analysis
- Skimming & Slimming:
 - Reduce number of events and information content



CHEP 2016: Proof of Principle

- Not changing the analysis workflow, optimizing the bookkeeping
 - Apache spark
 - Analyzer code in Scala
 - Input converted in Avro: <u>https://github.com/diana-hep/rootconverter</u>, stored on the HDFS



Two loops over file entries, parallel jobs in Spark across cluster

```
// Reference the whole dataset (not individual files)
val mcsample = avrordd("hdfs://path/to/mcsample/*.avro")
                                                                                 Input
// First pass (and cache for later)
mcsample.persist()
val mc sumOfWeights = mcsample.map(.GenInfo.weight).sum
                                                                                    Sum of Weights for Simulation
// Second pass on data in cluster's memory val result = mcsample.filter(cuts).map(toNtuple(_, mc_sumOfWeights, mc_xsec))
                                                                                                          Main Event
                                                                                                          Selection
// Save as ntuple
result.toDF().write.parquet("hdfs://path/to/mcsample_ntuple")
                                                                                       Output
              Output ntuple is used for analysis e.g: plots, fits, tables
                                                                                      Output contains information of:
# Bring the ntuple in as a DataFrame

    Object (e.g. Muon/Jet)

ntuple = spark.read.parquet("hdfs://path/to/mcsample_ntuple")

    Event (e.g. Luminosity)

ntuple.select("mass").show()
                                                                                        information
```

Physics plots!

Comparison

	Spark	ROOT
Analysis run without caching	9.4 sec	32.7 sec
Reading from local disk & Computation	4.3 sec	26.8 sec
Writing to local disk	5.1 sec	5.9 sec
Analysis run with caching	5.5 sec	
Reading from memory cache & Computation	0.4 sec	
Writing to local disk	5.1 sec	

- · Running both the Spark workflow and ROOT workflow on a single CERN Lxplus node, using one core
- Input files on local disk: 1 GB ROOT file, 2 GB AVRO file Caveat: ROOT file is compressed, AVRO is not

Conclusion: comparing performances not easy; spark is not order of magnitudes slower

Next steps

Thrust 1:

- Use analysis-specific data formats that have all recipes applied and framework code re-run
- Explore using Apache spark producing plots and tables

Thrust 2:

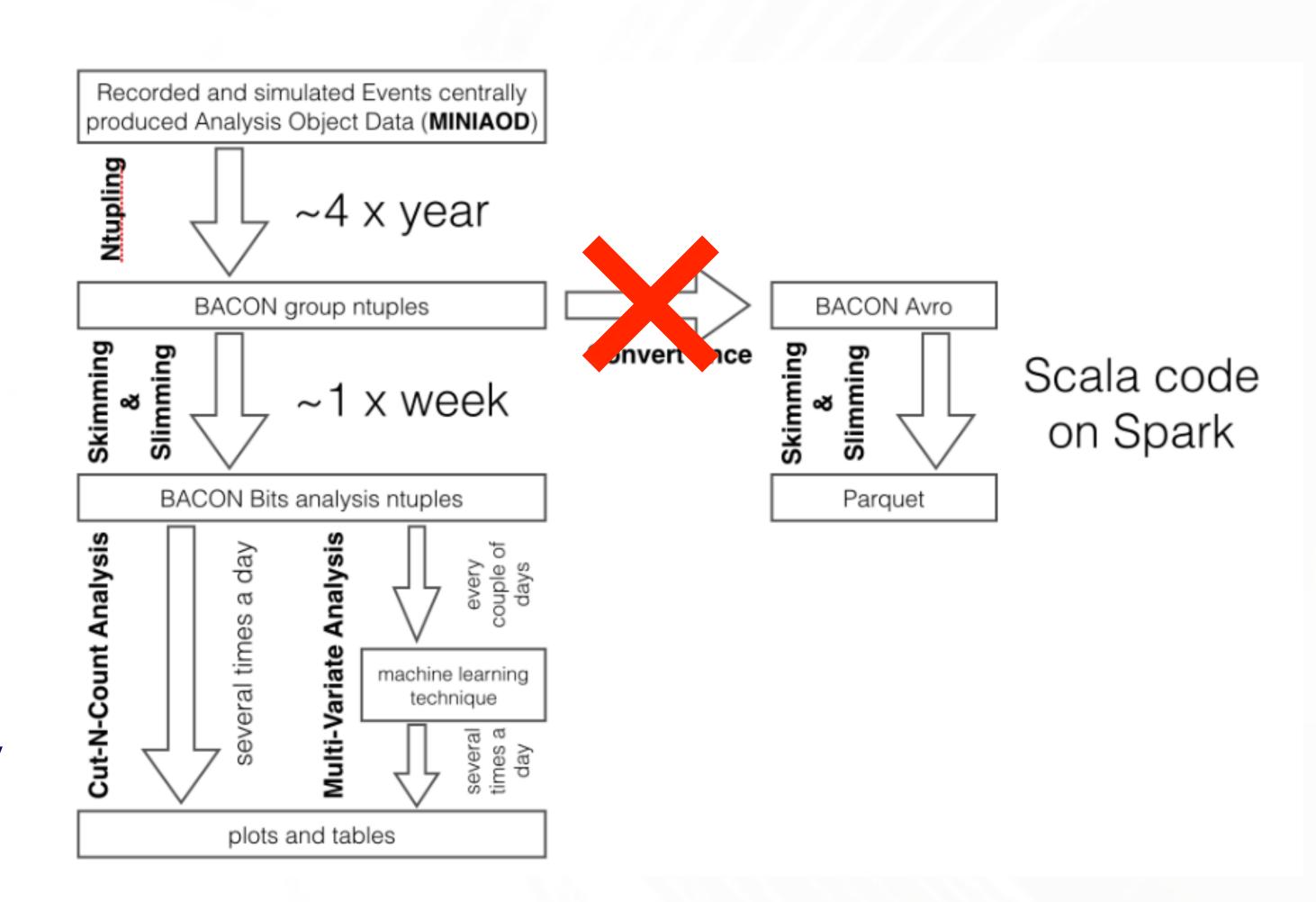
- Use official input
- Demonstrate reduction capabilities producing group analysis ntuples
- Goal: reduce 1 PB input to 1 TB output in 5 hours (CERN Openlab/Intel project)

Applying official recipes or re-running CMS framework code currently not being considered

Thrust 1

- https://github.com/diana-hep/ spark-root
- Read ROOT files directly from Apache Spark
 - Connect ROOT to Apache
 Spark to be able to read
 ROOT TTrees, infer the
 schema and manipulate the
 data via Spark's DataFrames/
 Datasets/RDDs.

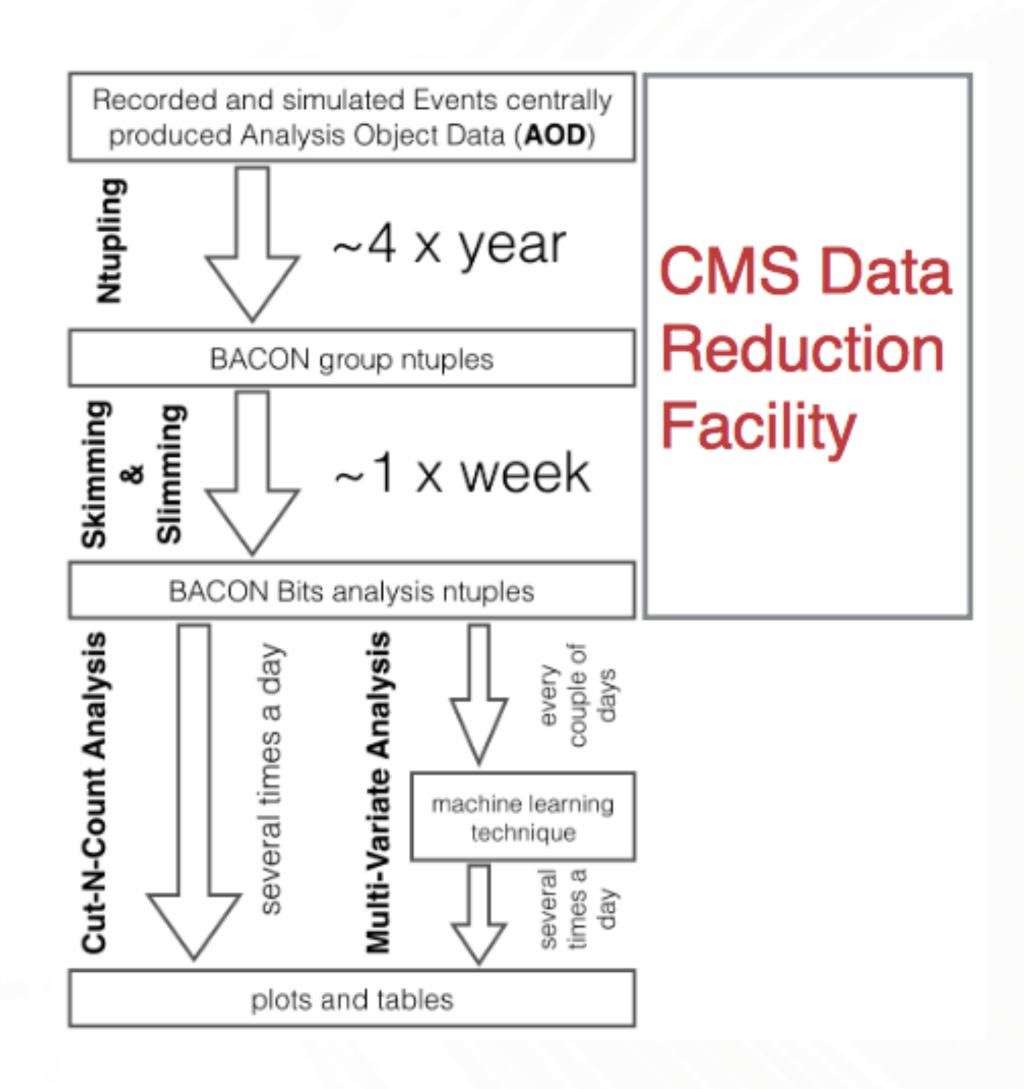
more in Jim's talk today



Thrust 2

Data Reduction Facility

- demonstrate the ability to reach at least a 1000 fold reduction in selected data
- perform this task roughly 100 times faster than it can currently be done
- · Goal:
 - Process an input sample of 1PB within 5 hours
 - Export a selected sample that is at least 1000 times smaller
- Work on CERN Hadoop using Spark
 - Started with using CMS open data
 - Copied small amounts to HDFS (currently using 1.2 TB)
- Next step: enable Spark to read ROOT files through sparkroot directly from HEP storage systems (EOS)



CMS Big Data Project

- Group created end of 2015
 - collaboration between FNAL, Diana-HEP, and CERN-IT
 - website: https://cms-big-data.github.io
- Rapidly expanding:
 - University of Padova and Bristol recently joined
- CERN Openlab enables partnership with industry:
 - CERN Openlab/Intel project called "CMS Data Reduction Facility"
 - Project includes CERN fellow supporting the development and testing of the reduction facility
 - Intel actively taking part in project
 - Sponsoring of CERN fellow included in the project

Backup